Optimization of e-Learning Model Using Fuzzy Genetic Algorithm

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ABSTRACT

E-learning model is examined of three major dimensions. And each dimension has a range of indicators that is effective in optimization and modeling, in many optimization problems in the modeling, target function or constraints may change over time that as a result optimization of these problems can also be changed. If any of these undetermined events be considered in the optimization process, this is called optimization problem. Many problems in the real-world are dynamic and uncertain and solve them as static are not appropriate. In this paper, for the first time a fuzzy genetic algorithm for optimization and modeling e-learning is presented. Method is that we create a fuzzy model at first, and then we perform optimization by genetic. The results of proposed algorithm on mobile peaks benchmark that are already best-known benchmark for evaluating in the modeling are evaluated and the results of several valid algorithms have been compared. The results indicate the high efficiency of the proposed algorithm in comparison with other algorithms.

Keywords: E-Learning Model, Fuzzy Logic, Optimization, Genetic Algorithm, Mobile Peaks Benchmark

1- Introduction

Fuzzy Genetic Algorithm (FGA*) is one of the algorithms are derived from nature and collective intelligence that is provided by doctor Li Xiao Lei in 2002 [1]. The algorithm is a collective behavior-based technique that is inspired by social behavior in nature. This algorithm has a high convergence speed characteristics, insensitive to initial values, high flexibility and fault tolerance. This algorithm is used in the applications of optimization such as learning of forward neural network, [2], data clustering [3], [4], data mining [5], optimization of nonlinear functions [6], [7], Combinational optimization [8] [9]....

Uncertainty in many real-world problems is quite clear and evident. One way of dealing with uncertainty is using collective intelligence and evolutionary methods. Uncertain problems that have already been studied by evolutionary methods in general can be divided into four categories; Noise in the evaluation function and being dynamic optimal solutions, perturbations in the design variables, being approximate the evaluation function and being dynamic optimal solutions. In this paper, the uncertainty of the type of being dynamic optimal solutions that is among the most common types of uncertainty is taken into consideration.

Several methods to solve modeling problems using evolutionary computing [10] and collective intelligence [11] methods are presented.

Two major problems of evolutionary computing methods that make lack of the ability direct use of these techniques to optimize in the modeling environment are invalid memory and diversity loss. When the model is changed, the resulted solutions in memory are not longer valid or they have completely forgotten or they can be assessed again.

Also, since most of the evolutionary computing and collective intelligence methods due to their nature are converging to a point, so cluster variety in the environment is lost and if changes in the environment converge to new optimal point, if possible, would be very time consuming.

Thus the basic requirements of optimization in the modeling environment can be used and correctly synchronize memory and also create a variety in the clusters after changes the model are considered.

This paper presents an FGA to optimize the e-learning model in which all requirements of modeling have been satisfied. In the proposed algorithm, fuzzy logic mechanism definition of law, establish a database [1] [7] [9] has changed. Also some parameters of FGA including crowding factor and step length were removed.

The proposed algorithm used on the Mobile Peak Benchmarks (MPB) *[12] that is the best known benchmarks in modeling and its performance with six other algorithms called mQSO [13], mCPSO [13], AmQSO [14], CellularPSO [15], SPSO [16], and rSPSO [17] are compared. Comparison benchmark is an Offline Error that is one of the main criteria to compare the algorithms is designed for dynamic environments [11]. Test results show that the proposed algorithm has acceptable performance.

Remaining of this paper is organized in the following way. The second section describes the proposed algorithm. Test results are discussed in the third section and the final section presents the conclusions.

2 - The Proposed Model

In this section, a new model based on fuzzy genetic algorithm for optimization in dynamic environments is presented. In this algorithm, behaviors and parameters and the process of performing FGA has been changed till the proposed algorithm can find the optimal model and following them after the changing environment. In the proposed algorithm three steps of fuzzication, modeling and optimization for e-learning model are done that has major differences with previous standard model [1] [7] [9]. Then, after describing a New Fuzzy Genetic Algorithm (NFGA), a new optimized model is introduced.

2-1 E-Learning Model Optimization Algorithm

First, we will describe the FGA step by step. E-learning model has three main dimensions of the following:

1 - Hard preparation

2 - Software preparation

3 - Coordination monitoring support preparation

Each of these dimensions, have smaller dimensions.

Software preparation, including nine other smaller dimensions named 1-security preparation, 2-policy preparation, 3- culture preparation, 4- human recourses preparation 5- financial preparation, 6- laws and regulations preparation, 7- content preparation, 8- standard preparation 9- management preparation.

Hardware preparation, including network preparation, equipment preparation and third dimensions includes: 1- Support Preparation 2- coordination preparation, 3- monitoring preparation. Each of these smaller dimensions is also included benchmarks in the attached table. These benchmarks are 116, which belong to a collection that is clear in the table. The table becomes fuzzy in the next section of modeling algorithm.

2-1-1 E-Learning Fuzzy Modeling

To fuzzication the proposed model Mamdani Inference **System** is used. In this system, for each dimensions and their characteristics fuzzy variable are defined. Then on each of these dimensions will form the base of fuzzy rules. It is should be noted the model in the software dimension has feedback then this dimensions will be considered as optimization criterion for genetic algorithm. Below you can see the fuzzy modeling.

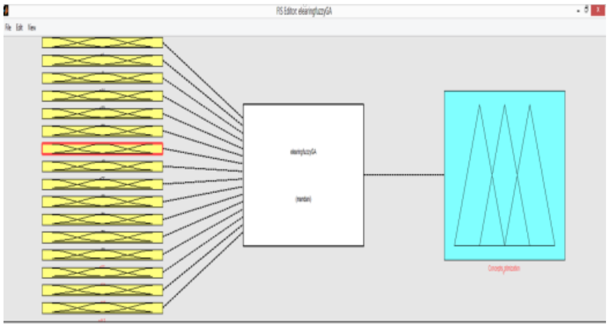

Figure 1 Model of e-Learning Fuzzy Rules

After the model is designed the rule base to determine associations between variables should be formed in form of fuzzy that the model of rule base is as follows.

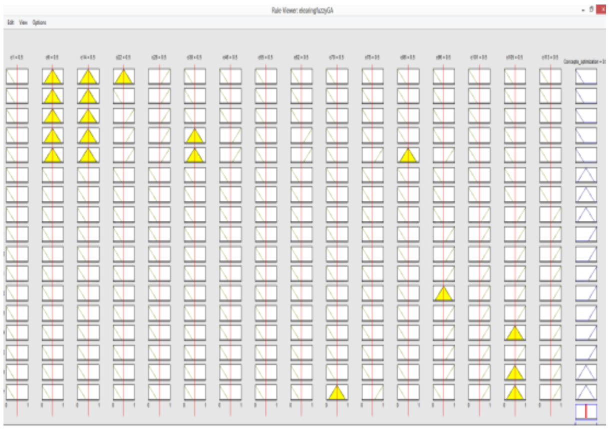

Figure 2 Model of Fuzzy Rules Base for e-Learning

Now results of the next section added to the genetic algorithm.

2-1-2Genetic Algorithm

As described in Section 1-1-2 for each indicators fuzzy model was defined in this section we explain how to apply genetic algorithms, general trend is that when the chromosomes were not able to shift into better positions, it does not move. In contrast to the standard model in the FGA if not find better positions in search behavior of model, randomly and freely move a step [1] and lose its previous position, in the FGA if fail , they retained their previous position. This makes the best of the cluster placed in the best position found so far by the members of the cluster because the behavior of the model in the FGA, only one chromosome is moved as to move into a better position.

In the behavior of following, each of the models a step towards the best cluster using equation 3:

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \frac{\vec{X}_{Best} - \vec{X}_i(t)}{Dis_{i,Best}} \times [Visual \times Rand(0,1)] \quad (3)$$

Where $\vec{X}_i$ is of i-th that performs the behavior of following and $\vec{X}_{Best}$ is equal to position vector of best cluster. Thus, the index of i-th maximum size of the visual (field of view) in each dimensions move toward the best cluster.

In fact, after an index to find more space other members of the cluster following that to achieve more space. Run the behavior of following the best cluster increases the speed of cluster convergence and helps to maintain consistency in a cluster. This behavior is group behavior and interaction between members of a cluster is done among all members of the cluster.

2-1-3- Collective Motion Behavior of Dimensions

This behavior is similar to behavior of following of a group behavior, and in the whole of the level of cluster members is done. In the group motion behavior, first of all the central position of cluster which is same center of gravity of cluster based on the arithmetic mean of all members of cluster in each dimension is calculated. To i-th index condition of move toward central position, which is f (XCenter) ≥ f (Xi) is checked, and if this was true, the next position of i-th index, using equation (4) is obtained:

$$(4)\quad \vec{X}_i(t+1)=\vec{X}_i(t)+\frac{\vec{X}_{Center}-\vec{X}_i(t)}{Dis_{i,Center}}\times\left[\vec{V}isual\times Rand(0,1)\right]$$

Equation 4 to move toward the central position which all the indexes of cluster that their situation is worse than the central position is used but for the best index of cluster is placed in the $\vec{X}_{Best}$ position, If the fitness value $\vec{X}_{Center}$ is better than $\vec{X}_{Best}$, next position of best indicator of the cluster is obtained by equation 5:

$$(5)\quad \vec{X}_{Best}=\vec{X}_{Center}$$

Equation 5 is used for best cluster because moving toward the central position using equation 4 may be placed in the worse position than its current position. There may be worse positions at the end of way toward the central position. As a result, this could result to loss of the best position ever found by all members of the cluster that using the equation 5 to best cluster this problem resolved. Reasons for not using equation 5 for all criteria of cluster is that transfer criteria of cluster into a identical position dramatically reduce the variation in the group and come down dramatically speed of convergence.

2-1-4- The Implementation of the Proposed Model

In the FGA for each of the indicators, in each repeats, each of optimal search behaviors, following and collective motion is performed. Unlike FGA standard that implementation one of both collective motion and following behavior had no effect on the optimal motion and a lot of calculations would be waste, in the FGA every three optimal search behaviors, following and collective motion in the displacement of the indicators and motion of cluster toward better positions are effective.

In the FGA all aspects of optimal search behavior is performed at first and their status is updated based on the implementation of the. With the implementation of this behavior, each dimension can have shift up try_number. Then all of them based on their new position and other clusters that performed the optimal search behavior would perform following behavior and all aspects except the aspect that has feedback (after soft preparation), will move into a new position in the way movement toward best position that found by the cluster.

At final, each aspect and indicators of the collective motion behavior is done. With the implementation of collective behavior, indicators that have remained away from the cluster are placed on worse position than other members of the cluster, more quickly returning to cluster. This behavior increases the speed of convergence and unlike the following behavior can even be improved best position of cluster.

2-2- Configuration of the Model as Optimization

In MPB, when there is more than one peak in the problem space, each peak can after change the setting to convert a global optimum, so all the peaks have to cover under aspects of e-learning model if any of them were to become a global optimization, algorithm able to find it quickly.

So at each peak shall be placed a cluster and covers it. In this paper, in the beginning there is only one cluster on the problem space, if this cluster is converging to a peak, another cluster comes up in the problem environment. When the cluster is converged the position of best indicator of cluster in the problem space after a few iterations is approximately fixed. When a cluster converged parameter value of the field of view is reduced to a cluster to do well local search in the vicinity of the target [9].

Each peak is only covered just under a cluster because increasing the number of clusters in a peak just consume an unreasonable of fitness assessment and as a result increase the speed of changing the environment than iterations of algorithm performance. So when both of them close to each other more than certain limit, that is, they have converged to a peak and therefore the cluster fitness of best dimension of that is less, then loss.

In the proposed algorithm, when all the dimensions in the problem environment were converged, a new cluster in the problem space is initialized. In each repeat, there should be only one free cluster. Free cluster is cluster that still not converged. When more than one cluster were free, only the best of them remain in the problem space and the rest are lost. After some implementation time passed all the peaks are covered and there will be a cluster free on the problem space.

To detect changes in the environment a random point in the first implementation algorithm are considered and amount of its fitness is recorded. In each repeat of the algorithm amount of fitness of this point is assessed and if it is different from the previous value it means the environment has changed. After detecting changes in the environment fitness of all artificial fish in all clusters is assessed and fitness value recorded for each artificial fish is valid and algorithm can then properly execute its behavior.

Then in each cluster, only the best indicator of cluster stays in its place and other members of the cluster within a certain radius around that are randomly distributed. Values of the radius equal to length of peaks displacement are considered. Thus, most likely after change the peak (target) is located within members' field of view. The act also increases the diversity in the cluster.

3- Test Results

To assess the accuracy and efficiency of the proposed algorithm, this algorithm with six known algorithms called mQSO [13], mCPSO [13], AmQSO [14], CellularPSO [15], SPSO [16] and rSPSO [17] on the MPB have been compared. Two algorithms m CPSO and mQSO with anti-convergence are given in the comparison as well. Results have been obtained with respect to scenario 2 in the MPB [12].

The only different parameter is the number of peaks for better assessment methods changed from 1 peak to 200 peaks at a change frequency of 5000 has been considered. In experiments, in the proposed algorithm indicators number of dimensions in each cluster equal to 2 and amount of Try_number equal to 1 are considered. Visual amount for those that have not converged equal to 20 and for those that have converged equal to 0.5 are considered. The value of this parameters based on experiments is set too high.

Experiments were performed 30 times and the results obtained from the experiments (Offline Error and Standard Error) on MPB with 100 times environment change at each experiment in the different peak number with environment changes of frequency 5000 in Table (2) shown. Standard Errors are shown in parentheses next to the Offline Error. Two best results in each row are highlighted and best result is in italic. P is equal to the number of peaks in these tables. Two algorithms with mQSO and mCPSO with anti-convergence marked with an asterisk.

As can be seen in the Table 2, the proposed algorithm in all cases has achieved better results than other algorithms. Since the number of clusters in the proposed algorithm determined based on the number of peaks, so efficiency of the algorithm in the low peaks is quite acceptable. This distinction exists in the AmQSO as well because in this algorithm the number of clusters determined based on the number of peaks is found but in the other algorithms due to the constancy of the number of clusters, when the number of clusters is greater than the number of peaks, clusters compare with each other over peaks and out together from the peaks using exclusivity, which thereby results were less than expected for the number of peaks.

For the proposed algorithm increasing the number of peaks decrease the performance of algorithm. The problem arises when there are a large number of peaks; there will be more clusters in the problem space. Increasing the number of clusters, the number rises to evaluate the fitness of each iteration, since the frequency change of e-learning model is based on amount of fitness assessment, it causes the dimensions has less iteration till changes subsequent environment. As a result, the accuracy of search can lower and the results encountered decrease in the quality.

AmQSO algorithm encountered this problem more than proposed algorithm and the number of peaks 100 and 200 its performance is also less than previous model i.e. mQSO in which the number of categories is fixed. In the proposed algorithm, due to the rapid increase in diversity after environment change and quickly cover peak, results from the higher number of peaks encountered less quality loss.

4- Conclusion

This article for first time proposes a new method for e-learning fuzzy modeling and optimization procedure was performed by genetic algorithm. And its results on the mobile peaks benchmarks function were compared with several other well-known methods. Results shown that the proposed algorithm has acceptable performance in all cases, i.e. has effect on both low number of peaks and high number of peaks

Table (2): Offline Error and Standard Error of the algorithms in the 5000changes frequency with different peaks numbers

P	Cellular PSO	mCPSO*	mQSO*	rSPSO	SPSO	proposed algorithm
1	2.55(0.12)	4.93(0.17)	5.07(0.17)	1.42(0.06)	2.64(0.10)	**0.79(0.06)**
5	1.68(0.11)	2.07(0.08)	1.81(0.07)	1.04(0.03)	2.15(0.07)	**0.86(0.05)**
10	1.78(0.05)	2.08(0.07)	1.80(0.06)	**1.50(0.08)**	2.51(0.09)	**0.94(0.04)**
20	2.61(0.07)	2.64(0.07)	2.42(0.07)	2.20(0.07)	3.21(0.07)	**1.09(0.05)**
30	2.93(0.08)	2.63(0.08)	2.48(0.07)	2.62(0.07)	3.64(0.07)	**1.30(0.02)**
40	3.14(0.08)	2.67(0.07)	2.55(0.07)	2.76(0.08)	3.85(0.08)	**1.90(0.04**
50	3.26(0.08)	2.65(0.06)	2.50(0.06)	2.72(0.08)	3.86(0.08)	**1.81(0.06)**
100	3.41(0.07)	2.49(0.04)	**2.36(0.04)**	2.93(0.06)	4.01(0.07)	**1.92(0.05)**
200	3.40(0.06)	2.44(0.04)	**2.26(0.03)**	2.79(0.05)	3.82(0.05))	**1.03(0.06)**

References

1. Darab, b., (2011). “An electic model for assessing e-learning readiness in the Iranian universities”.
2. Asgharpour, M.J., (1386). “Group Decision Making and Games Theories with Operation Research View”.
3. Bingham, R., (1388) “Student Skills”, Science and Technology University.
4. Tayefeh, M. M., (1382). “Training and Improving Operational Skills as an Electronic Learning Service in Learning Environment”, a set of articles of the first Information Technology and Knowledge International Conference, Tehran, December.
5. Asgharpour, M. J., (1386). “Group Decision Making and Games Theories with Operation Research View”.
6. Fallown, K.l, Brown, Sh., Bagheri, F., Kouchak Mehdi, H., (1387). “Electronic Learning Standards”, Tehran, Madares Houshmand Publication.
7. Deylmaghani, M.,(1386). “Challenges and Necessities”, a Member of Scientific Board of University Department of Industries Engineering University.
8. Toloui Ashlaghi, A., (1387). “Expert System”, University Courses, Science and Research University.
9. Tehrani, S., Tadayon, Sh., (1380). “Information Technology Management”, Tehran, First publish.

10. Hakimipour, A., “Decision Making in Management”, second publish.
11. Afshar Kazemi, M. A., (1387). “Expert Decision Making”, Science & Research University.
12. Whitman, M.E. and Mattord, H.J. (2009). "Management of information security", Thomson, second edition.
13. Bhaskar, S.M., and Ahson, S.I. (2008)."Information security A practical Approach," Alpha science.
14. Turban, E., and Aronson, J.E, and Liang, T.P.,(2007). "Decision support systems and Intelligent systems," prentice- Hall, seven Edition, 2007.
15. Alter, S., (2004)."Information systems", pearson Education, fourth Edition.
16. Whitman, M.E., and Mattord, H.d., (2006)."Readings and cases in the management of Information security ,ISEN
17. Withman, M.E. and Mattord, H.d., (2003)."Hands – on Information security lab Manual", second Edition.
18. Williams, A.H.,; "In a trusting environment, everyone is responsible for information security.
19. Krutz, R.l., and Vines, R.D., (2007). "The CISM prep Guide: Mastering the five Domains of Information security management". John wiley & sons, ISBN: 0471455989.
20. Rahim, A. and Basir, otman; Hassanein, khaled (2005). "An Intelligent Decision support system For Layout system.
21. Decenzo, D. (2002) "Human Resource Management" Stephen. P. Robins.
22. Harrison, Tobias; wennstorm, Daniel (2006) ."A Decision support system for Executive Business management" ABB.
23. Pouruakhshouri, Z., and shattri, M., (2003)." Decision support system In oil spill cases" Disaster prevention and management volume 2, Nubmber 3.
24. Serpell A., and Maturana, S., (2002)."A Decision supoort system for Human Resource Management In construction Projects.
25. Swanepoel, K., (2007). "Decision support system: Real – Time Control of manufacturing processes" Journal of manufacturing Technology management, volume is, number 1